# Medical Image Compression by Using Discrete Haar Wavelet Transform

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Abstract: Medical image compression is very useful and has a great significance nowadays for data storage and easy transfer of data or images between two points. In order to transfer images its first required to be compressed at the transmitting point and upon being reached to destination decompression process is done to reconstruct the original image or an approximate of it. In this paper we introduce the best way of compressing medical images by using Discrete Haar Wavelet Transform DWT. Many research have been done in image compression techniques among of the methods used are Discrete Cosine Transform, Gaussian Pyramids, Block Truncation Coding and Singular Value Decomposition.

Keywords: Image Compression, Discrete Haar Wavelet Transform [DWT], Coding redundancy, CWT, PSNR.

## 1. Introduction

From last few decades, the increasing demand of storage and transmission of digital images, image compression is now become an essential application for storage and transmission [1]. Demand for communication of multimedia data through the telecommunications network and accessing the multimedia data through Internet is growing explosively [2]. Not only that but also in the medical field there was an increase of data needed to be stored and transmitted to different points and through that image compression became more popular.

The main objective of image compression is to reduce irrelevance and redundancy of the image data in order to be able to store or transmit data in an efficient form. Several image compression techniques have introduced to solve various image compression problems but until now the best is by using Discrete Haar Wavelet transform.

Different redundancies that are used to compress the image signal are Coding Redundancy, Inter-pixel Redundancy and Perceptual Redundancy.

## 2. Background

The first literature that relates to the wavelet transform is Haar wavelet. It was proposed by the mathematician Alfred Haar in 1909. However, the concept of the wavelet did not exist at that time. Until 1981, the concept was proposed by the geophysicist Jean Morlet. Afterward, Morlet and the physicist Alex Grossman invented the term wavelet in 1984. The first DWT was invented by Hungarian mathematician Alfred Haar. For an input represented by a list of  $2^n$  numbers, the Haar wavelet transform may be considered to pair up input values, storing the difference and passing the sum. This process is repeated recursively, pairing up the sums to provide the next scale, which leads to  $2^n - 1$  differences and a final sum.

Image compression can be lossy or lossless [13, 14]. In a lossless compression algorithm, compressed data can be used to recreate an exact replica of the original; no

information is lost to the compression process. While lossless compression is useful for exact reconstruction, it generally does not provide sufficiently highcompression ratios to be truly useful in image compression.

Image compression systems mainly consists of two distinct structural blocks which are encoder and decoder [10]. Usually an image f(x, y) is fed into encoder and the encoder creates the set of symbols from input data and uses them to represent the image. If we let n1 and n2 be the number of information carrying units in the original and encoded images respectively then the compression ratio can quantified numerically using the method below:-



A general image compression system block diagram

**Mapper:** Transforms the input data into a (usually nonvisual) format designed to reduce interpixel redundancies in the input image. This operation is generally reversible and may or may not directly reduce the amount of data required to represent the image.

**Quantizer:** Reduces the accuracy of the mapper's output in accordance with some pre-established fidelity criterion. Reduces the psych visual redundancies of the input image. This operation is not reversible and must be omitted if lossless compression is desired.

Symbol (entropy) encoder: Creates a fixed- or variablelength code to represent the quantizes output and maps the

# Volume 5 Issue 9, September 2016

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The general image compression block diagram JPEG 2000 (a) Encoder and (b) Decoder

## 3. Discrete Haar Wavelet Transform

Discrete Haar wavelet compression is an efficient way to perform both lossless and lossy image compression. It relies on averaging and differencing values in an image matrix to produce a matrix which is sparse or nearly sparse. A sparse matrix is a matrix in which a large portion of its entries are 0. A sparse matrix can be stored in an efficient manner, leading to smaller file sizes. The DWT of a signal is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response resulting in a convolution of the two:

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k]$$

The signal is also decomposed simultaneously using a highpass filter. The outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other and they are known as a quadrature mirror filter.

$$\begin{array}{c} & & & \\ & & & & \\ & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & &$$

However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist's rule. The filter outputs are then subsampled by 2. Then g- denotes high pass and h- low pass as is Mallat's and the common notation:

$$egin{aligned} y_{ ext{low}}[n] &= \sum_{k=-\infty}^\infty x[k] h[2n-k] \ y_{ ext{high}}[n] &= \sum_{k=-\infty}^\infty x[k] g[2n-k] \end{aligned}$$

This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled.

$$(y \downarrow k)[n] = y[kn]$$

The above summation can be written more concisely.

 $egin{aligned} y_{ ext{low}} &= (x st g) \downarrow 2 \ y_{ ext{high}} &= (x st h) \downarrow 2 \end{aligned}$ 

However computing a complete convolution with subsequent down sampling would waste computation time. The lifting scheme is an optimization where these two computations are interleaved.

## 4. Image Compression by Using Discrete Haar Wavelet Transform

The discrete wavelet transform has a huge number of applications in science, engineering, and mathematics and computer science. Most notably, it is used for signal coding, to represent a discrete signal in a more redundant form, often as a preconditioning for data compression. The Discrete Wavelet Transform (DWT) has become a powerful technique in biomedical signal processing [5]. As DWT provides both octave-scale frequency and spatial timing of the analyzed signal, it is constantly used to solve and treat more and more advanced problems.

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the continuous wavelet transform (CWT), or its implementation for the discrete time series sometimes called discrete-time continuous wavelet transform (DT-CWT).



Filter banks used for decomposition and reconstruction. (a)
Filter bank used to decompose a 2D signal into its approximation and its vertical, horizontal and diagonal coefficients. (b) Filter bank used to reconstruct a 2D signal from its approximation and wavelet details

## 5. Compression Steps

The steps needed to compress an image are as follows:

1) Digitize the source image into a signal s, which is a string of numbers.

# Volume 5 Issue 9, September 2016

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- 2) Decompose the signal into a sequence of wavelet coefficients w.
- 3) Use thresholding to modify the wavelet coefficients from w to another sequence w'.
- 4) Use quantization to convert w' to a sequence q.
- 5) Apply entropy coding to compress q into a sequence e.

#### Digitization

The first step in the wavelet compression process is to digitize the image. The digitized image can be characterized by its intensity levels, or scales of gray which range from 0 (black) to 255 (white), and its resolution, or how many pixels per square inch.

#### Thresholding

In certain signals, many of the wavelet coefficients are close or equal to zero. Through a method called thresholding, these coefficients may be modified so that the sequence of wavelet coefficients contains long strings of zeros. Through a type of compression known as entropy coding, these long strings may be stored and sent electronically in much less space.

There are different types of thresholding. In hard thresholding, a tolerance is selected. Any wavelet whose absolute value falls below the tolerance is set to zero with the goal to introduce many zeros without losing a great amount of detail. There is not a straightforward easy way to choose the threshold, although the larger the threshold that is chosen the more error that is introduced into the process. Another type of thresholding is soft thresholding.

Once again a tolerance, h, is selected. If the absolute value of an entry is less than the tolerance, than that entry is set to zero. All other entries, d, are replaced with sign (d) ||d| - h|. Soft thresholding can be thought of as a translation of the signal toward zero by the amount h. A third type of thresholding is quantile thresholding. In this method a percentage p of entries to be eliminated are selected. The smallest (in absolute value) p percent of entries are set to zero.

#### **Entropy Coding**

Wavelets and thresholding help process the signal, but up until this point, no compression has yet occurred. One method to compress the data is Huffman entropy coding. With this method, and integer sequence, q, is changed into a shorter sequence, e, with the numbers in e being 8 bit integers. The conversion is made by an entropy coding table. Strings of zeros are coded by the numbers 1 through 100, 105, and 106, while the non-zero integers in q are coded by 101 through 104 and 107 through 254. In Huffman entropy coding, the idea is to use two or three numbers for coding, with the first being a signal that a large number or long zero sequence is coming. Entropy coding is designed so that the numbers that are expected to appear the most often in q, need the least amount of space in e.

#### Quantization

The fourth step of the process, known as quantization, converts a sequence of floating numbers w' to a sequence of integers q. The simplest form is to round to the nearest integer. Another option is to multiply each number in w' by a

constant k, and then round to the nearest integer. Quantization is called lossy because it introduces error into the process, since the conversion of w' to q is not a one-toone function.

Denoising and the compression procedure contains three steps:

1) Decomposition.

- Detail coefficient thresholding. For each level from 1 to N, a threshold is selected and hard thresholding is applied to the detail coefficients.
- 3) Reconstruction.

#### a) Advantages of DWT Over CWT

- 1) The discrete wavelet transform (DWT), on the other hand, provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time.
- 2) The DWT is considerably easier to implement when compared to the CWT.

#### b) Disadvantages Of DWT

- 1) For fine analysis, it becomes computationally intensive
- 2) Its discretization, the discrete wavelet transform (comp. efficient), is less efficient and natural
- 3) It take some energy to invest in wavelets to become able to choose the proper ones for a specific purpose, and to implement it correctly.

#### c) Applications Of Wavelet Transform

Wavelets transform are a powerful statistical tool which can be used for a wide range of applications, namely,

- 1) Signal processing
- 2) Data compression
- 3) Smoothing and image denoising
- 4) Fingerprint verification
- 5) Biology for cell membrane recognition, to distinguish the normal from the pathological membranes
- 6) DNA analysis, protein analysis
- 7) Blood-pressure, heart-rate and ECG analyses
- 8) Finance (which is more surprising), for detecting the properties of quick variation of values
- 9) In Internet traffic description, for designing the services size
- 10) Industrial supervision of gear-wheel
- 11) Speech recognition
- 12) Computer graphics and multifractal analysis

## 6. Simulation Results

Simulation results are presented for the image compression with Discrete Haar wavelet transform at different levels of decomposition. Medical images used here are all in grayscale format.

#### CT-scan images of the human lungs

Volume 5 Issue 9, September 2016



Figure 1: Image compression at decomposition level n=1



Figure 2: Image compression at decomposition level n=2



Figure 3: Image compression at decomposition level n=3



Figure 4: Image compression at decomposition level n=4



**Figure 5:** Image compression at decomposition level n=5 **Table of results obtained** 

| S. | Decomposition | Compression   | PSNR value between |
|----|---------------|---------------|--------------------|
| No | level n       | ratio         | original image and |
|    |               | in percentage | compressed image   |
| 1. | 1             | 28.0735       | 27.8435            |
| 2. | 2             | 32.8190       | 28.1401            |
| 3. | 3             | 33.6533       | 28.1777            |
| 4. | 4             | 33.9260       | 28.1709            |
| 5. | 5             | 33.7976       | 28.1558            |



#### CT-scan images of the human brain



Figure 6: Image compression at decomposition level n=1



Figure 7: Image compression at decomposition level n=2



Figure 8: Image compression at decomposition level n=3



Figure 9: Image compression at decomposition level n=4

Volume 5 Issue 9, September 2016

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Figure 10: Image compression at decomposition level n=5

| Table of results obtained |               |             |                    |  |  |
|---------------------------|---------------|-------------|--------------------|--|--|
| S. No                     | Decomposition | Compression | PSNR value between |  |  |
|                           | level n       | ratio in    | original image and |  |  |
|                           |               | percentage  | compressed image   |  |  |
| 1.                        | 1             | 31.1906     | 26.8366            |  |  |
| 2.                        | 2             | 34.4046     | 26.9493            |  |  |
| 3.                        | 3             | 34.8657     | 26.9329            |  |  |
| 4.                        | 4             | 34.7800     | 26.9482            |  |  |
| 5.                        | 5             | 34.5822     | 26.9292            |  |  |



## 7. Conclusions

In this paper image compression was done at different decomposition levels n, the compression ratio in percentage and PSNR value between the original image and compressed imagecalculated and the results tabulated. Therefore medical image compression using discrete haar wavelet transform is necessary and efficient way for storing medical images and transmitting images.

## References

- [1] Rafael C. Gonzalez, Richard E. woods, "Digital Image Processing", Third Edition, Prentice Hall.
- [2] Subramanya, "Image Compression Technique," Potentials IEEE, Vol. 20, Issue 1, pp 19-23, Feb-March 2001.
- [3] Discrete Wavelet Transforms Algorithms and Applications Edited by Hannu Olkkonen.
- [4] The Wavelet Tutorial Part IV by ROBI POLIKAR
- [5] World of Computer Science and Information Technology Journal (WCSIT) Vol. 4, No. 9, pp.127-132, 2014
- [6] Journal of Physical Sciences, Vol. 13, 2009, pp.121-134
- [7] IJCSI International Journal of Computer Science Issues, Vol. 9, Issue 4, No 1, July 2012 pp. 327-330

- [8] BULLETIN (New Series) OF THE AMERICAN MATHEMATICAL SOCIETYN Volume 28, Number 2, April 1993
- [9] Feature Extraction & Image processing for Computer Vision, Third Edition by Mark S.Nixon and Alberto S. Aguado
- [10]Digital image processing using Matlab by Rafael C. Gonzalez, Richard E.Woods and Steven L. Eddins
- [11] Conceptual wavelets in Digital Signal Processing An indepth practical approach for Non-mathematician by D. Lee Fugal
- [12] International Journal of Computer Technology and Electronics Engineering (IJCTEE) Volume 3, Special Issue, March-April 2013.
- [13] M. J. Weinberger, G. Seroussi and G. Sapiro, "The LOCO-I lossless image compression algorithm: Principles and standardization into JPEG-LS", IEEE Trans. on Image Processing, Vol. 2, pp. 1309-1324, Aug. 2000.
- [14] Madhuri A. Joshi, "Digital Image Processing, AnAlgorithmic Approach", PHI, New Delhi, pp. 175-217, 2006.

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2319

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